Locally Equivalent Weights for Bayesian MrP

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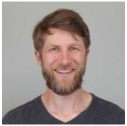  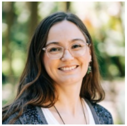 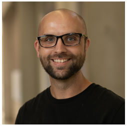 

Future work

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But the high level idea can be extended much more widely:

1. Assume your initial model was accurate
2. Select some perturbation your model should be able to capture
3. Use local sensitivity to detect whether the change is what you expect
4. If the change is not what you expect, either (1) or (2) was wrong

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Checks of this form can recover generalized versions of many standard diagnostics for linear models.

Future work

Regression bias:

$$y = \theta^\intercal \mathbf{x} + \varepsilon$$
$$\tilde{y} = (\theta + \delta)^\intercal \mathbf{x} + \varepsilon$$
$$\hat{\theta}(y) \overset{\text{check}}{=} \hat{\theta}(\tilde{y}) + \delta$$

Regression residual exogeneity:

$$\tilde{y} = y + \varepsilon z$$
$$\hat{\theta}(y) \overset{\text{check}}{=} \hat{\theta}(\tilde{y})$$

Regression fisher information:

$$\mathcal{I} := \text{Fisher information}$$
$$\Sigma := \text{Score covariance}$$
$$\mathcal{I}^{-1} \overset{\text{check}}{=} \Sigma$$

General models “bias check”

$$y = f(\mathbf{x}, \varepsilon, \theta)$$
$$\tilde{y} = f(\mathbf{x}, \varepsilon, \theta + \delta)$$
$$\hat{\theta}(y) \overset{\text{check}}{=} \hat{\theta}(\tilde{y}) + \delta$$

General models “exogeneity check”:

$$y \sim \mathcal{P}(y|\mathbf{x}) \text{ and } \mathcal{P}(\mathbf{x}) = w$$
$$\tilde{w} = w + \delta$$
$$\hat{\theta}(\tilde{w}) \overset{\text{check}}{=} \hat{\theta}(w)$$

General models “information check”:

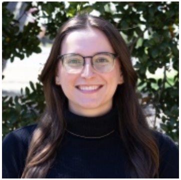
$$y \sim \mathcal{P}(y|\theta)$$
$$\tilde{y} \sim \text{Importance sample using } \tilde{w} \text{ where}$$
$$\tilde{w} = \frac{\mathcal{P}(y|\hat{\theta} + \delta)}{\mathcal{P}(y|\hat{\theta})}$$
$$\hat{\theta}(\tilde{w}) \overset{\text{check}}{=} \hat{\theta}(1) + \delta$$

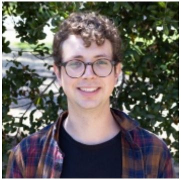
Future work

Student contributions and ongoing work:

- **Vladimir Palmin** is working on extending MrPlew to `lme4`
- **Sequoia Andrade** is working on generalizing to other local sensitivity checks
- **Lucas Schwengber** is working on novel flow–based techniques for local sensitivity
- **(Currently recruiting!)** Doubly–robust Bayesian Hierarchical MrP


Vladimir Palmin


Sequoia Andrade


Lucas Schwengber

Preprint and R package (hopefully) coming soon!

References i